Development of an Induced Seismicity Susceptibility Framework and Map for NEBC using an Integrated Machine Learning and Mechanistic Validation Approach

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Summary

A key recommendation in the Scientific Review of Hydraulic Fracturing in British Columbia report (Allen et al., 2019), was for a susceptibility map of induced seismicity potential be developed for NEBC. A similar map was developed in 2018 for the Duvernay Play in Alberta and in 2020 for Montney Play using machine learning (Pawley et al., 2018, Wozniakowska and Eaton, 2020). However, the map produced was limited to the data relationships determined by computer algorithms without connecting these to cause and effect mechanisms, for example characteristic fault behaviour. The goal of this research project is to first address the Panel's recommendation to develop an induced seismicity susceptibility map for NEBC. Several machine learning algorithms will be tested to investigate the robustness of each and to provide recommendations and guidelines on their use. The machine learning phase will then be followed by a mechanistic validation phase, where the machine learning output will be refined to add confidence by using a combination of controlled laboratory experiments and 3-D numerical simulations to account for known cause and effect relationships. The outcome of this project will be to deliver a more robust susceptibility map to help decision makers with their planning of hydraulic fracturing activities and induced seismicity hazard management planning. It will also help identify areas requiring additional focused research.

Workflow

We compared the performance of multiple machine learning models on classification of seismogenic wells and regression analysis of maximum magnitude and number of associated induced events to each well. The components of the machine learning analysis workflow are shown in Figure 1.

In this analysis machine learning models were generated using SciKit-learn (Pedregosa et al., 2011) which is a machine learning library for the Python programming language. The workflow of model generation includes: First, data quality assurance and control with outlier removal. Next, data imputation is used to fill some of the missing data and at the end of this step all data are scaled to have zero mean with unit variance. Before moving to model training and validation, Exploratory Data Analysis (EDA) is performed to summarize the main characteristics of data and determine which evaluation metric should be used when comparing different models' performances. The final step of model generation is model tuning and training.

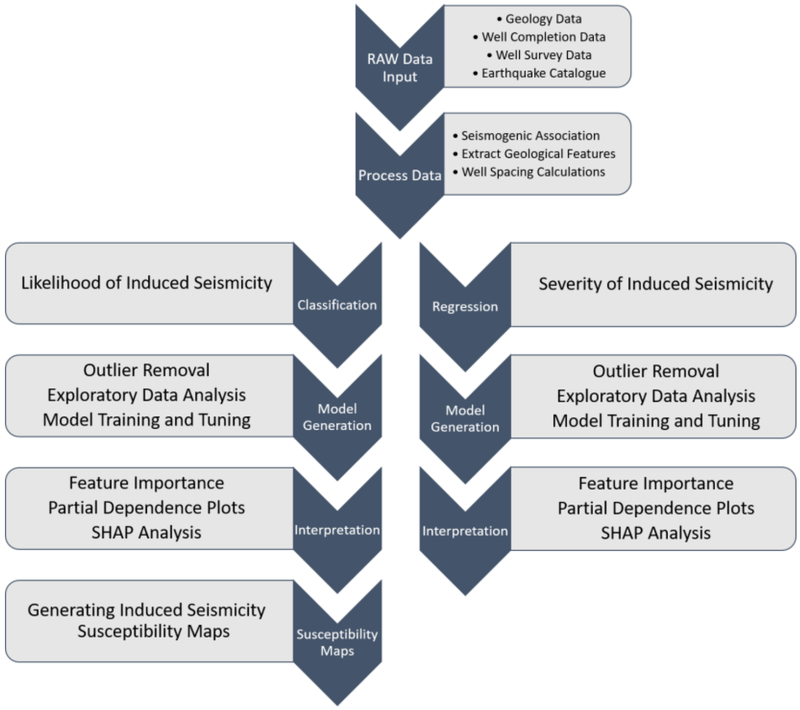

Figure 1- Analysis workflow

Results

Based on the results of classification model validation, Light GBM and Random Forest models were selected as best performing models for this task. To generate the susceptibility maps the probabilities of induced seismicity at 2.5 km grid points were calculated and afterwards interpolated within Montney Formation’s border to create a raster. The generated maps are shown in Figure 2. From generated maps it is seen that the output of Light GBM model is concentrated and rough with majority of map containing probabilities between zero and 10 percent. In contrast, Random Forest model’s output are more spread and smoother. Both models show good agreement with the identified susceptible areas and locations of induced seismic events (not shown in Figure 2).

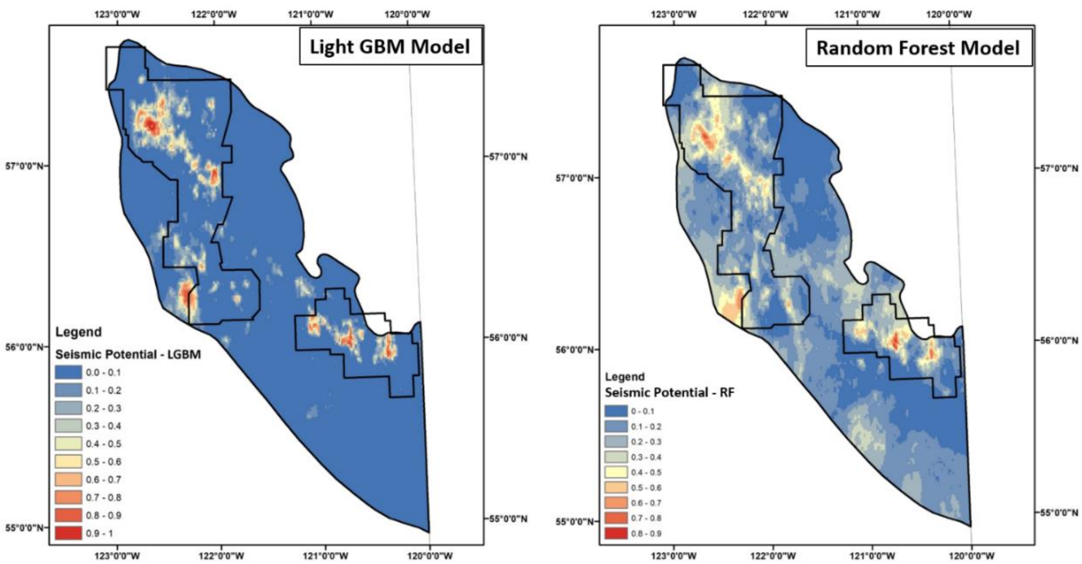

Figure 2-Induced seismicity susceptibility maps based on (a) Light GBM (b) Random Forest models

Acknowledgements

This work is financially supported by Geoscience BC and geoLogic. The authors would like to thank Enlighten Geoscience Ltd. and Petrel Robertson Consulting Ltd. for data support and Itasca for providing XSite numerical modelling software.

References

Allen, D., Eberhardt, E., & Bustin, A. (2019). Scientific Review of Hydraulic Fracturing in British Columbia. Report by the Scientific Hydraulic Fracturing Review Panel to the B.C. Minister of Energy, Mines and Petroleum Resources.

Pawley, S., Schultz, R., Playter, T., C., H., S., T., L., & Hauck, T. (2018). The geological susceptibility of induced earthquakes in the Duvernay play. Geophysical Research Letters, 45, 1786–1793. https://doi.org/https://doi.org/10.1002/ 2017GL076100

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, ´Edouard. (2011). Scikit-learn: Machine Learning in Python. Journal of Machine Learning Research, 12, 2825–2830. https://doi.org/10.1145/2786984.2786995

Wozniakowska, P., & Eaton, D. W. (2020). Machine Learning-Based Analysis of Geological Susceptibility to Induced Seismicity in the Montney Formation, Canada. Geophysical Research Letters, 47(22). https://doi.org/10.1029/2020GL089651